Revisiting the JDL Model for Information Exploitation

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Abstract—The original Joint Directors of Laboratories (JDL) model was developed in the early 90's, with revisits in 1998, and 2004. Today, with new technologies of big data, cloud computing, and machine analytics, there is an ever increasing need for integration of people and machines. The original JDL model focused on the data fusion (correlation, filtering, and association) issues, while today there is an increasing emphasis on an integrated approach to information exploitation over sensors, users, and missions using enterprise architectures, interoperability standards, and intelligence to the edge. Given these recent changes to computation and distributed access, we examine ways for extending the JDL model from 1998 to support exploitation functions and information management for situation awareness, massive data analytics for contextual awareness, and domain-specific needs for mission awareness.

Keywords: JDL model, enterprise architectures, data fusion, information management, contextual reasoning

I. Introduction

This paper is meant to serve as a re-examination of the use of the Joint Directors of Laboratories (JDL) model [1, 2, 3, 4, 5] to meet the needs for fusion processing that is responsive to new technologies of big data, cloud computing, and machine analytics. The inception of the original JDL Data Fusion model aimed at providing a process flow for sensor and data fusion [1]. Subsequent revisions were made in 1998 [2] to incorporate new understanding of the issues involved in exploiting information for diverse purposes such as impacts versus threats and process refinement versus sensor management. There also were needs to clarify terms, broaden the model from its initial focus on tactical military applications, and apply to different users [3]. With the establishment of the International Society of Information Fusion (ISIF), the notion of "information" became an important concept in IF designs and analysis. In 2004, the JDL model was revised as per the issues discussed from the working group [4, 5]. At the same time, from the working group, there was the proposed Data Fusion Information Group (DFIG) model, which included suggested updates from the constituent member discussions such as a focus on user functions [6]. The focused application of this paper deals with information exploitation of distributed multimedia content which requires revisions of the JDL model for machine analytics, information management, and user contextual reasoning over enterprise applications.

Since the 1990 book of *Multisensor Data Fusion* [7], the process flow for "fusion" has been about the same. However, with the popularity of the web and the formation of ISIF (www.isif.org), new developments have resulted from information exploitation and "management" [8]. These developments affect the existing models. An accepted modeling distinction has been made between high-level information fusion (HLIF) and low-level information fusion (LLIF) which was first described in [7]. The low-level functional processes support target classification, identification, and tracking, while high-level functional processes support situation, impact, and fusion process assessment. LLIF concerns numerical data (e.g., target locations, kinematics, and attribute types). HLIF concerns abstract symbolic information (e.g., threat, intent, and goals) [9]. Over the last decade, there have been numerous panel discussions on HLIF that demonstrate the ever changing issues in systems-level information fusion [10]. Some recent systems issues include new methods for evidential reasoning [11], situation awareness logic [12], enterprise architectures [13], interface management [14], and distributed architectures [15]. A complete list of interesting modifications to the use of the JDL functional model can be found in hundreds of papers in the ISIF conferences.

The focus of the paper is aimed at those who are building information fusion systems that support information exploitation (InfoEx). InfoEx from many sensors and users distributed across a variety of locations requires a revisit to the JDL model for system-based applications. For a closed-loop sensor system, the tenets of the original JDL process flow are applicable with real-world parameters (e.g., a Kalman Filter). For InfoEx systems, which are envisaged to have multiple users, data sources, intelligence data collections, missions, and different users, the JDL model can be used for guidance, but has to be adapted to meet these needs. A large-scale system is difficult to comprehensively model, and thus, provides a notional representation of the process flows across parameters and conditions as done in [4].

The key goal of [4] was to clarify definition of terms and establish a clear and generalized basis for the JDL model. It defined data fusion as 'the process of combining multiple pieces of data to estimate the state of some aspect of the world. Partitioning into data fusion "levels" was stated in terms of the types of such aspects: L0: features, L1: individual

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14. ABSTRACT

The original Joint Directors of Laboratories (JDL) model was developed in the early 90?s, with revisits in 1998, and 2004. Today, with new technologies of big data, cloud computing, and machine analytics, there is an ever increasing need for integration of people and machines. The original JDL model focused on the data fusion (correlation, filtering, and association) issues, while today there is an increasing emphasis on an integrated approach to information exploitation over sensors, users, and missions using enterprise architectures, interoperability standards, and intelligence to the edge. Given these recent changes to computation and distributed access, we examine ways for extending the JDL model from 1998 to support exploitation functions and information management for situation awareness, massive data analytics for contextual awareness, and domain-specific needs for mission awareness.

15. SUBJECT TERMS

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entities, L2: structures (e.g., relationships and situations), L3: scenarios and outcomes, and L4: aspects of the system itself. Sensor and other information management functions were partitioned into a series of analogous levels. The model is a functional model and therefore agnostic as to whether implementation of any of these functions is by people or automated processes [2]. Extending the JDL model to encompass resource management with data fusion supports functions of problem-solving under uncertainty. System designers and process managers may want a tight integration of diverse fusion, data mining, adaptive modeling, sensing and diverse resource management processes.

Information exploitation considers the utility of information, probability of acquiring such information via candidate action plans and costs of plans, all of which are time-dependent (utility and cost are also user variables). InfoEx involves considerations of the characterization and representation of utility and cost, multi-agent and multi-user systems, and adaptive management and adaptive context exploitation.

Steinberg states [16, 17]:

> *Context provides expectations, constrains processing, and can infer or refine desired information ("problem variables") on the basis of other available information ("context variables")*

A key issue of utilizing context relates to the original distinction of low-level information fusion (LLIF) and High-level Information Fusion (HLIF). In the *Data Fusion Information Group* (DFIG) model (see Fig. 1), LLIF (L0-1) composes explicit object assessment. HLIF (L2-6) composes much of the discussions and changes in the last decade [6].
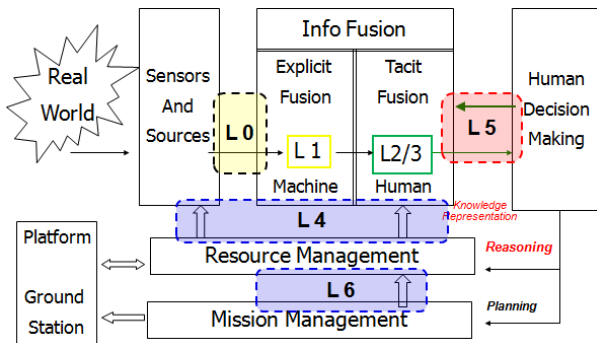

Figure 1 - DFIG Information Fusion model (L = Level). [6]

In the DFIG model, the goal is to utilize the Data Fusion and Resource Management (DF/RM) functions proposed in the 1998 revisions, while highlighting the user's involvement. Humans are active observers with the ability to reason over contextual information [18]. RM is divided into fusion process control (L4), user refinement (L5), and platform placement/resource collection (L6), and to meet mission objectives. L2 Situation Assessment (SA) includes structures and relationships which are inferred from L1 Object Assessment of individual entities from L0 Data Alignment (i.e. registered features). Since unobserved SA events are difficult for a computer to assess, user knowledge and reasoning are necessary. L3 (Impact Assessment) includes scenarios, outcomes, sense-making of threats, courses of action, optimal decisions obtained using game theory [19],

estimation of intent, etc. to help refine the SA estimation and information needs for different actions.

Motivations: The DFIG model suggestions were revisits to the original JDL model during the 2004 discussions. For example, the user requires different tasks utilizing various skills (perception), rules (tasks) and cognition (knowledge) [20]. Also, many fusion systems are designed to meet a specific mission. Thus, the Level 5/6 are distinct as to represent the different interactions, tailor the information fusion design to different systems, and address the advancements in the use of information fusion by the general community. However, there are practical limitations to the DFIG model.

Limitation 1: The L1 (explicit machine fusion), L2/3 (implicit machine fusion) and interface to human (L5) are not unique. Processes at any of these levels can include explicit, implicit, human or machine approaches [6]. A better distinction than explicit/implicit is between (1) *filtering/refinement* which converts an input estimate of a random variable to a more accurate or less uncertain estimate of that variable, and (2) *inference/abstraction* which estimates (frequently latent) variables from those available as inputs.

Limitation 2: From Fig. 1, the choice to combine L2/L3 based on common functions needs to be separated based on variables extracted for exploitation. Distinguishing (L1, L2, L3) as data fusion functions (blocks) and (L0, L4, L5, L6) as resource management functions (interfaces) does not characterize that these blocks and interfaces represent fusion and control exploitation processes. For example, cognitive reasoning (L5) to constrain control could also be evidential reasoning (L2) for fusion. Planning, typical done by humans through automation is now afforded through autonomy with enterprise resources. Finally, the platform of sensors and ground stations should encompass other enterprise resources (e.g., World Wide Web) with varying degrees of controllability over not just the implied physical "real world", but perhaps the "external universe of discourse" to cover virtual realities.

Major suggestions since the 2004 revisions are the focus on information management, advanced visualizations, data mining, and mission focus with teams, priorities, and coordination. All of these functions help to *establish context* for the HLIF unsolved issues of fusion and resource management. For example, RM can be aided by information management enterprise computing (aspects of data acquisition, access, recall, and storage services).

The rest of the paper is organized as follows. Sect. II discusses the information management enterprise with system level (or processing) context information. Sect. III describes machine analytics, and Sect. IV discusses user refinement in contextual analysis. Sect. V presents a notional example of data processing using physics-derived (e.g. video) and human-derived (e.g. text) fusion for both a JDL-type instantiation and suggestions for the JDL-based information exploitation. Discussions and conclusions are presented in Sect. VI.

II. INFORMATION MANAGEMENT ENTERPRISE

In this section, we detail the enterprise, information management, and layered service constructs to support management and exploitation of information of context.

A. Information Fusion Modeling in the Enterprise

The current trends in information fusion (IF) are *data mining*, *enterprise architectures*, and *communications* [21]. Different mission applications require coordination over (1) data: models, storage/accesses control, and process and transport flow, (2) architectures: (e.g. service-oriented architecture), and (3) the enterprise (e.g. service bus, computing environment, and the cloud). Fig. 2 highlights the needs of the user, elements of data mining [22], and data flow in the enterprise.

Information exploitation involves two processes (1) integrating and managing the data, and (2) analyzing the data through IF and data mining. The JDL model deals only with part of data analysis as IF. Services and clouds can deal with the implementation of these two steps as represented in Fig. 2.
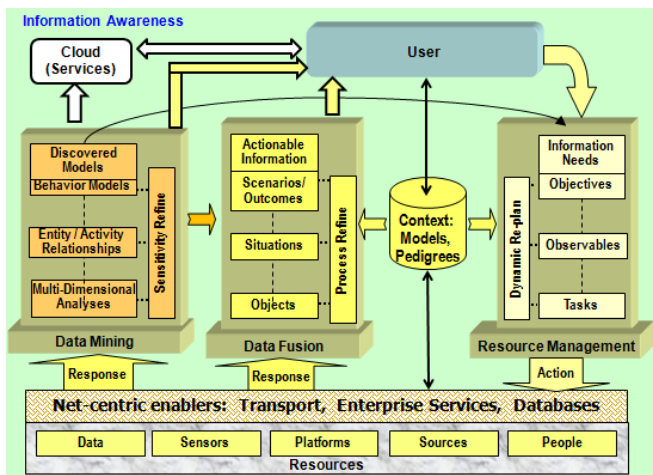

Figure 2 – Information Fusion Enterprise Model (Adapted from [23])

Context is both input and output of data analysis. For example, context (e.g., terrain and background traffic) is used to support fusion (e.g., finding usual behavior) and at the same time is the output of fusion (e.g., terrain from fusing video). Recently, Solano and Jernigan [13] presented an enterprise architecture to manage intelligence products for mission objectives highlighting data formats (e.g., schemas, unstructured, and metadata); data processes (e.g., access, ingest, cleansing, profiling, and ontology workflows); and database management services (DBMS). DB resources include contextual information such as terrain models. Cloud technology can serve as a basis for access to DB resource information but requires access (e.g., service-oriented architecture (SOA)) to enterprise services.

B. Information Management (IM) Model

The goal of IM is to maximize the ability (effectiveness) of a user to act upon information that is available to, produced, or consumed within the enterprise. There are several means by which this can be accomplished:

- Reducing barriers to effective information use by providing notification, mediation, access control, and persistence services;
- Providing an information space wherein information is managed directly, rather than delegating IM responsibilities to applications that produce and consume information;
- Focusing on consumer needs rather than producer preferences to ensure that information can be effectively presented and used;

- Providing tools to assess information quality and suitability;
- Exploiting producer-provided characterization of information to support automated management and dissemination of information [9]; and
- Tools for goal-driven search, discovery and exploitation of information to meet dynamic information needs.

Optimal users' ability/effectiveness achieved by any of these means can make applications less complicated and enables the enterprise to be more agile to adapt to changing requirements and environments.

There are several best practices that help achieve the goals of information management. Organizations will greatly improve the interoperability and agility of their future net-centric information fusion (and command and control) systems by:

1. Adopting dedicated information management infrastructures (e.g., cloud computing);
2. "Packaging" information for dissemination and management,
3. Creating simple, ubiquitous services that are independent of operating system and programming language;
4. Using a common syntax and semantics for common information attributes such as location, time, and subject; and
5. Adopting interfaces among producers, consumers and brokers that are simple, effective and well-documented

If appropriately employed, these best practices can reduce the complexity of information fusion systems, allow for effective control of the information space, and facilitate more effective sharing of information over an enterprise environment.

Fig. 3 presents an IM model which illustrates the extended relation of the actors coordinating through the enterprise with the various layers and inner circles providing the protocol for information service access and dissemination [9].
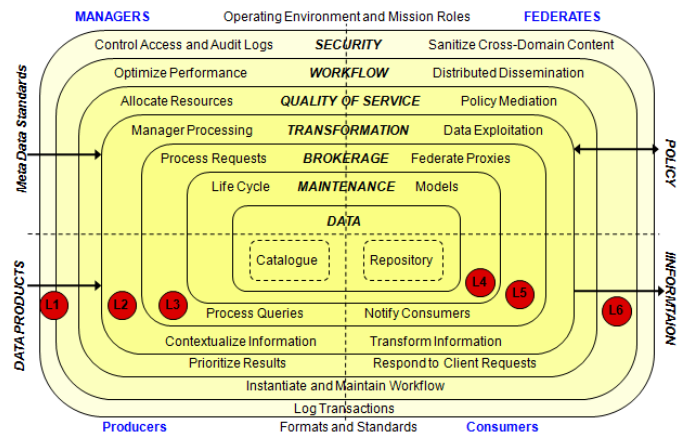

Figure 3 – Information Management (IM) Model.

People or autonomous agents interact with the managed information enterprise environment by producing and consuming information or by managing it. Various actors and their activities/services within an IM enterprise surround the IM model that transforms data into information. Within the IM model, there are various services that are needed to process the managed information objects (MIOs).

A set of service layers are defined that use artifacts to perform specific services. An artifact is a piece of information that is acted upon by a service or that influences the behavior of the service (e.g., a policy). The service layers defined by the

model are: Security, Workflow, Quality of Service (QoS), Transformation, Brokerage, and Maintenance, as shown in Table 1. These services are intelligent agents that utilize the information space within the architecture, such as cloud computing and machine analytics.

Table 1: Service Layers

Security	Control access, Log transactions, Audit logs, Negotiate security policy with federated information spaces, Transform identity and Sanitize content
Workflow	Manage workflow model configurations, Instantiate and maintain workflows, Assess and optimize workflow performance
QoS	Respond to client context, Allocate resources to clients, QoS policy mediation, Prioritize results, and Replicate information
Transformation	Contextualize information, Transform MIOs, Support state and context-sensitive processing, Support user defined processing functions, Support manager defined processing functions,
Broker	Process queries, Support browsing, Maintain subscriptions, Notify consumers, Process requests for information and advertisements, Support federated information space proxies
Maintenance	Post MIOs, Verify Adherence to standards, Manage MIO lifecycle, Manage information space performance, Retrieve specific MIOs from repositories, Support configuration management of information models

One recent technology development is cloud computing which supports an enterprise analysis [23, 24].

C. Layered View of the Cloud

Using elements of the JDL/DFIG, the enterprise, and the IM model for sensing, networking, and reporting can be realized. Fig. 4 presents the layered information where the end-user (operator or machine) desires quality information as fused products from data which requires various methods and services from sensor collections to information delivery. "Sensors/Sources" can be viewed as a general term as it relates to physical sensors, humans, and database services (e.g., data mining) that seek data from the environment.

Current trends in information fusion share common developments with cloud computing such as agent-based network service architectures [25], ontologies [26] and metrics [27] to combine physics-derived sensing and human-derived reporting using fusion products.
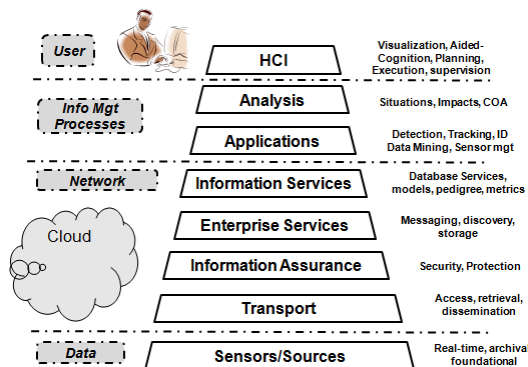

Figure 4 – Layered Information Services.(adapted from Kessler, White 2008)

D. Systems-Level Management of Context

The JDL model is a functional model that seeks to identify and organize mathematical fusion functions; with management functions evident in all levels of the model. Three issues that have been addressed as inherent at each level are:

- *Uncertainty management through contextual awareness*, and particularly, management of second-order uncertainly. This involves issues of source characterization (particularly with human sources), representation of diverse flavors of uncertainty, as well as computational issues (e.g. in PHD-based methods) [28, 29, 30].
- *Adaptive context exploitation*, considering the utility of information, probability of acquiring such information via candidate action plans and costs of plans, all of which are time-variable (utility and cost are also user-variable). This involves considerations analogous to the above: consistent characterization and representation of utility and cost. Additional factors include multi-agent and multi-user systems. Aspects of this problem are the integration of fusion, mining and general problem solving methods, adaptive process, model, and goal management, and adaptive context exploitation [31, 32].
- *Methods of user involvement through contextualization*, to include the interface and control issues for specific tasks that are operationally divided amongst different users such as information collection, real-time control, forensic analysis, and visualizations. These functions are local functions distributed over a large team for specific tasks versus a single user that is responsible for the entire information fusion system[33, 34, 35].

The JDL variations of the Signals, Feature, Decision (SFD) Model [7], (DF/RM) dual-node architecture [2], the User-Fusion Model (UFM) [36], Transformation of Requirements for Information Process (TRIP) model [37], and State-Transition Data Fusion (STDF) [9] each seek common processes across many levels and a more robust way of implementation by re-use of data and methods to serve different purposes. The method of *context* has also been a subject of these model developments and variations that have influenced developers using the JDL as a framework for implementation. For the DF/RM model, context is divided into those elements that support data fusion (L0-3), and those for management (L4). An example is terrain information in which tracking can be adapted to road information and sensors can be managed as related to zones of authorized operation. The TRIP model divides the problem into demand conditioning (L4-6) and supply conditioning (L0-3). The demand/supply duality is meant to serve users requesting information and the system determining if these requests can be answered. For demand conditioning, decision, exploitation, and observability context are used to decompose the user request into machine functions (i.e., fusion) that can be processed. The UFM seeks to utilize the users cognitive requests (L5-6) in establishing context in their coordination of the fusion levels (L0-4). Finally, the STDF utilizes the same control (L4-6) to look over different functions such as physics-derived (e.g. radar) (L0-1), human-derived (e.g. text) (L0-1), situations, (L3), and scenarios (L4). The key attributes of these JDL variants are inherent in establishing different methods of fusion and control with common issues described at each level.

The future of the use of JDL will require developments in uncertainty analysis, exploitation, and user involvement based on the context, such as mission management (L6). While these related models (SDF, UFM, TRIP, DF/RM, STDF) all have elements of context, they also try to solve real problems for real users. Hence, a current trend in information processing is

machine analytics that seeks methods of data compression and presentation for user interaction.

III. MACHINE ANALYTICS

In the JDL model revisits in 2004, little attention was paid the enormous amount of types of data (e.g. email and sensor), distributed locations, and various connections to different applications (e.g. finance to surveillance) that have resulted from the expansion of the World-Wide Web. Related concepts recently emerging are machine, descriptive, prescriptive, predictive, visual, and other analytics yet to be coined. There are three issues of importance *hardware* (e.g., Apache Hadoop data intensive distributed architecture), *software* (e.g., machine analytics), and *user/domain* applications (e.g. visual analytics, text analytics). Since the JDL is a functional model, we will focus on the last two. Data Mining (DM) and data fusion (DF) are analysis functions supported by machines.

A. Modeling Analytics

The commercial business industry has been managing large volumes of transactional data using powerful databases systems and, most recently, using cloud infrastructures. Traditional business analytics has focused mostly on descriptive analyses of structured historical data using statistical techniques. The current trend in DM is towards *predictive analytics* of unstructured data such as documents, video, image sets, multimedia data, network data, matrices, tensors, and graphs and tensors [38]. The field of data fusion [39] has been making use of cutting edge Artificial Intelligence (AI) and Machine Learning (ML) techniques to perform situation and threat assessments. Given that analytics and data fusion are two sides of the same coin, an effective revision of the JDL model warrants a close cooperation between the two communities in terms of technology enrichment for managing and intelligent processing of large volumes of data. The model extensions should be able to seamlessly exploit such enriched technologies in areas such as massive data analytics, hybrid reasoning, text analytics, and distributed processing.

Traditional statistical approaches are invaluable in data-rich environments, but there are areas where AI and ML approaches provide better analyses, especially where there is an abundance of subjective knowledge. Benefits of such augmentation include mixing of numerical and categorical variables in algorithms, "what-if" or explanation-based reasoning, explainable results of inferences easily understood by human analysts, and efficiency enhancement incorporating knowledge from domain experts as heuristics to deal with the "curse of dimensionality". Though early AI reasoning was primarily symbolic in nature (i.e., manipulation of linguistics symbols with well-defined semantics), it has moved towards a hybrid of symbolic and numerical, and therefore one is expected to find probabilistic and statistical foundations in many AI approaches. Conversely, business analytics traditionally has powerful customer or other related segmentation techniques via various powerful clustering algorithms such k-means, hierarchical clustering and k- nearest neighbor. Table 2 depicts some of the well-known techniques categorized along the statistics, AI and ML paradigms along with a special category for temporal reasoning given the dynamic nature of analytics and fusion

problems. Here are some examples of augmentation and enrichment of business analytics:

- Enrich principal component and factor analyses with subspace methods (e.g., latent semantic analyses);
- Meld regression analyses with probabilistic graphical modeling;
- Extend autoregression and survival analysis techniques with Kalman filter and dynamic Bayesian networks, embed decision trees within influence diagrams; and
- Augment "nearest-neighbor" and *k*-means clustering techniques with support vector machines and neural networks.

Table 2. Approaches to Modeling Analytics

Paradigm	Approach	Technologies
Statistical	Non-deterministic relationships between variables are captured in the form of mathematical equations and probability distributions	Test hypothesis, regression analyses, probability theory, sampling, inferencing
Artificial Intelligence	Domain experts provide knowledge of system behavior, and knowledge engineers develop computational models using an underlying ontology	Logic-based expert systems, fuzzy logic, Bayesian networks
Temporal	Linear/nonlinear equations specify behavior of stochastic processes or of dynamic systems as state transitions and observations	Autoregression, survival analysis, Kalman filters, Hidden Markov Models, Dynamic Bayesian Networks
Machine Learning	System input/output behavior is observed, and M techniques extract system behavior models	Clustering, neural network, and various linear, nonlinear, and symbolic approaches to learning

Machine analytics (MA) covers the broad spectrum of applications and provides a direct link to the traditional JDL model. Processes that require machine data analysis include: physics-derived sensor (e.g., video), human-derived (e.g., text), and machine (e.g., web files) data. MA is also based on the processes of man-machine and machine-machine interactions. Inside MA are the emerging concepts of (1) descriptive, prescriptive, predictive analytics, and (2) scientific, information, and visual analytics. These concepts mirror discussions in the current JDL model revisits of information exploitation.

The business oriented definitions of analytics complement elements of data fusion.

- *Descriptive Analytics* looks at an organization's historical and current performances which can be used to diagnose the situation.
- *Predictive Analytics* forecasts future trends, behavior and events for decision support such as to suggest courses of action profile and trending.
- *Prescriptive Analytics* determines alternative courses of actions or decisions options (using predictive information), given the historical, current and projected situations and a set of objectives, requirements, and constraints [40].

Visual analytics (VA) [41] seeks scientific, information, and cognitive representations. Visualization supports analytical reasoning, planning, and decision making through effective data representations and transformations over physical- and human-derived data (sometimes referred to hard and soft data fusion). Finally, user interaction with machines is important for the collection, exploitation, and dissemination of data.

- Scientific visualization deals with data that has a natural geometric structure (e.g., MRI data, wind flows).

- Information visualization handles abstract data structures such as trees or graphs.
- Visual analytics is especially concerned with sensemaking and reasoning.

If we look at "analytics" (Table 3) it mirrors the JDL (and other proposed models – DFRM and DFIG) in having both the data fusion *reasoning* (e.g., Bayes) and systems-level *management* (e.g., control) functions. Thus, the MA is like reasoning, while VA is about management.

Table 3. Machine Analytics Mapped to Information Fusion Levels

Fusion	Machine	Concept
Level 0	Scientific	Access to data and pedigree of information and issues of structured/unstructured data
Level 1	Information (Visual, text)	Development of graphical methods for data analysis
Level 2	Descriptive	Uses data mining to estimate the current state (i.e. Machine learning) over different reasoning of trends for modeling
Level 3	Predictive	Future options from current estimates
Level 4	Prescriptive	Sequencing of selected actions
Level 5	Visual	Sensing Making and Reasoning
Level 6	Activity-Based	Policy instantiation of desired outcomes as to a focused mission

B. Data Fusion Analytics

Descriptive and Predictive Analytics together establish current and projected situations of an organization, but do not recommend actions. An obvious next step is *Prescriptive Analytics*, which is a process to determine alternative courses of actions or decision options, given the situation along with a set of objectives, requirements, and constraints. Automation of decision-making of routine tasks is ubiquitous, but subjective processes within organizations are still used for complex decision-making. This current use of subjectivity should not prohibit the fusion and analytics community from pursuing a computational approach to the generation of decision options by accounting for various non-quantifiable subjective factors together with numerical data. The analytics-generated options can then be presented, along with appropriate explanations and backing, to the decision-makers of the organization.

Systems routinely collect and store large volumes of data on a continuous basis from a variety of disparate and heterogeneous sources. Though such distribution is coherent with recent thrusts towards net-centric warfare, analysts often face a daunting task when searching for specific data or for series of correlated data residing in distributed sources. One solution is to build a large centralized data storage area in advance, such as a cloud infrastructure. However, the proprietary nature of some of the sources requires that they operate autonomously and hence a distributed fusion approach [42] is vital.

There are also other types of analytics: (1) *Web Analytics*: internet usage data for purposes of understanding and optimizing web usage, and business and market research; (2) *Image Analytics*: real-world videos and images to extract information with machine performance comparable to humans; and (3) *Cross-lingual Text Analytics*: Analytics with contents in multiple languages that enable a system to discover and maximize the value of information within large quantities of text (open-source or internal). The growing trend in analytics serves at DF/DM for both autonomy (machine) and automation (machine to user).

IV. USER INVOLVEMENT

The *Observe-Orient-Decide-Act (OODA) model* serves as another common widely used model, and referenced in the information fusion community. As differentiated from the IM Model which deals with the enterprise and distribution of the data, the OODA is focused on a local control loop. Both of these models are useful for information fusion and can be enhanced with InfoEx capabilities such as visual analytics.

The ODDA model serves as a good basis for an operator; but updates have appeared with multiple OODA loops: TECK-OODA [43], C-OODA [44], and (Us versus Them) [45]. For example in Fig. 5, a real-time operator is reactive; whereas an analyst has more time for data mining and discovery.
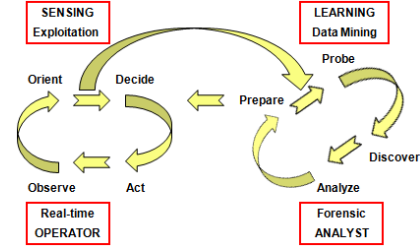

Figure 5 – Multiple OODA Loop Human/Machine Interactions.

Using multiple OODA loops [46, 47], there are two types of cases where an operator is making real-time decisions and an analyst is making forensics non-real time assessments. The motivation is based on the paradigms of (A) getting inside the enemy's control loop (L3), and (B) team decision making (L5). Obviously, the selection of the competitor, such as in game theory [19], requires determining a focused threat (L6). What is extended from the JDL and variations [48] is highlighting real-time versus the non-real time data mining and machine analytics for adaptive information exploitation.

V. ANALYSIS OF INFORMATON EXPLOITATION

With the JDL and advances in computation, there is a need to focus on the HLIF management functions such as managing the amount of information available. Current developments in enterprise architectures support information management, cloud computing, user refinement through queries, and machine analytics. For *contextual reasoning*, much of the ancillary data is available on a distributed enterprise system to provide situational analysis focused on mission needs. One example is that a user would like to refine the estimates of many target tracks and uses semantic queries (ontology) to access the database through machine analytics /data mining.

A. Context Tracking with Physics & Human-derived data

We designate two types of data: video and user text (e.g., documents). The physics-derived video can be processed by a machine; however, the human-derived text can be processed by a machine, but still needs user involvement to understand the meaning of the connected words.

Information fusion developments include large data (e.g., imagery), flexible autonomy (e.g., from moving airborne platforms over communication systems), and human

coordination for situation awareness [49]. Fig. 6 demonstrates an imagery data collection example using electro-optical (EO) cameras and Wide-Area Motion Imagery (WAMI). Using information fusion for situation awareness based on imagery includes: (i) tracking targets in images (fusion over *time*) [50], (ii) identifying targets using different sensors (fusion over *frequency*) [51], and (iii) linking target measurements over wide areas (fusion over *space*) [52]. Enterprise information includes stored data of the physical (terrain), resource (sensors), and social context (objects) that is easily accessible from cloud services.
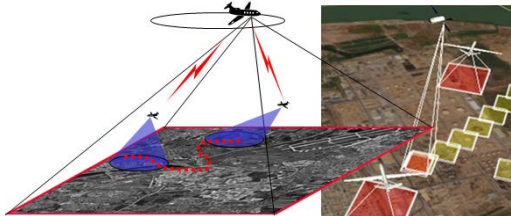

Figure 6 - Wide Area Motion Imagery (WAMI) data.

Given WAMI [53, 54] data, shown in Fig. 6, we seek the benefits that are enabled from an enterprise network. For example, when the user designates an area of interest, the machine can then detect and track targets (L1 fusion) and access contextual information through data mining (L2/L3 fusion) to enhance understanding (e.g., target type, identification (ID) and activity). Finally, the results are used to query the sensors to get more information (L4 fusion), store the results, present to the user (L5 fusion) and disseminate back to the cloud for mission awareness (L6 fusion).

B. Information Management Contextual Tracking

In *scenario 1*, raw (images, text), filtered (tracks, keywords), and fused (tracks with classification and ID labels) are sent to user stations. For the five cases (1-5), we model data scaled to the relative volume values. We assume that there five distributed operators are maintaining surveillance. The complexity from Case 1 to Case 5 is akin to tracking a few targets (8 = 40/5) to that of trying to maintain tracks over the entire context of a city (200 tracks = 1000/5). For users, they need information fusion support to track these many targets.

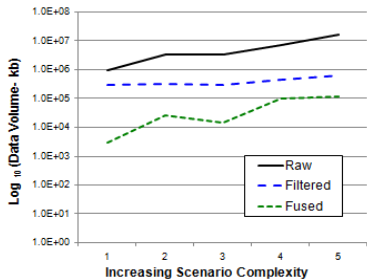| Scenario 1				Scenario 2 (data in K)				
Case	Video	Text	Tracks	Case	Users	Raw	Filtered	Fused
1	3	10	40	A	1	946	310	3
2	10	500	40	B	3	3332	334	15
3	10	50	200	C	5	3196	332	26
4	20	500	1000	D	8	6884	455	99
5	50	1000	1000	E	10	16340	653	115

Figure 7 – Traditional JDL Data Fusion

Assuming raw data messaging, it is intuitive that the filtered information can reduce the volume by ruling out unnecessary data (see Fig. 7). The results indicate that from the traditional JDL methods, there is little to no information management from the user, mission, or machine analytics.

In the *second notional scenario*, we are interested in seeing the benefits of user involvement, machine analytics, and information management to support distributed users. Not all users require the same collection information; however they can query the information they need from the cloud to be presented on their displays. In this case, we use a publish/subscribe (Pub/Sub) architecture to afford the interactions of distributed users.

Using Pub/Sub information management, it is important to note that over a different set of users desiring situational context, with two data feeds (video to tracks and text to keywords) and 40 to 200 tracks, there is a break point in operations. For this case, if you try and normalize over the time duration of the scenario, the fused information accounts to three pieces of information for each image. For the case of two operators, they can follow more objects by specializing in the data source and area of designated interest to highlight tracks. The interesting part is the difference between 5 to 10 operators in that there is an order of magnitude more information being passed around as many users (assumed) are requesting the same information.

The notional Scenario 2 speaks to team management. With too many operators looking at similar data, there could be overlap in functions. Using contextual information and user-defined operating pictures (UDOP) displays, information can deliver machine analytic results to the appropriate user. Each UDOP provides a tailored situational display and the user can call the raw, filtered, or fused data. For this scenario, we compare the filtered and fused data as the user does not want the raw data.
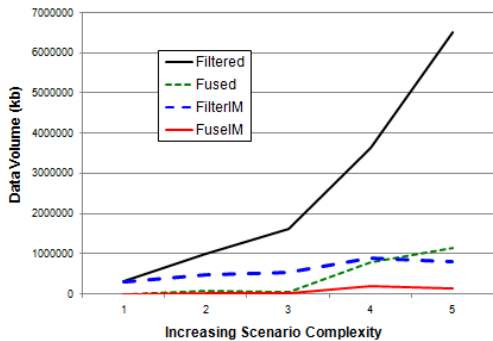

Figure 8 – Data Fusion with info exploitation.

Fig. 8 demonstrates possible needs to extend the JDL model. In this case, using information management sends the correct data to the correct user (by request) for user assessment. However, using the combination of information fusion and contextual awareness in a pub/sub enterprise, only the fused data is going back and forth – saving volumes of data transactions. Here, we assume such things as visualization (versus the entire filtered image and text), resident overhead imagery to overlay tracks and text reports at the distributed site, and command and control interfaces that allow each user to know the updates from the other users.

VI. CONCLUSIONS

Since the inception of the JDL model, it has served as a process model to explain information fusion. This paper revisits the JDL based on technology developments in the last decade as discussed in the ISIF community. We highlight three information exploitation technology developments affecting the JDL model that include: (1) an enterprise architecture that supports information management to store and access data through cloud computing, (2) machine analytics for data mining, and (3) man-machine interfaces to support users as active observers of contextual reasoning (L5).

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